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Letters to the Editor

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APPLICATION OF NEURAL NETWORK APPROACH TO IMPROVE THE QUALITY OF INSAT DERIVED QUANTITATIVE PRECIPITATION ESTIMATES

1. Satellite observations of infrared (IR) and microwave radiance have been used successfully to retrieve precipitation information over many parts of the glove. Satellite derived Quantitative Precipitation Estimates (QPE) promise to provide a very useful input for the initialization and validation of Numerical Weather Prediction (NWP) models (Krishnamurti *et al.*, 1995; Roy Bhowmik and Prasad, 2001). But the accuracy of the product is limited due to the indirect relationship of the cloud top temperature and precipitation. It has been well established by various studies (Janowiak, 1992; Ebert and Marshall, 1995; Roy Bhowmik and Sud, 2003) that QPE suffers from many technical and scientific issues. There are various key factors like topography, prevailing synoptic situation and its interactions with mesoscale systems, stratiform precipitation; calibration issues which posses uncertainties in deriving QPE from satellite data sets. The study of Roy Bhowmik and Sud (2003) showed that the rainfall over most part of Indian monsoon region is significantly under-estimated due to the fact that rainfall rate constant (72 mm/day) as introduced by Arkin *et al*. (1989) is unrealistically low in the context of intense mesoscale convective rainfall in association with monsoon depression or cyclone storm.

During recent years, the technique of Artificial Neural Network (ANN) has drawn considerable attention towards handling this kind of complex and non-linear problems. The technique has been widely applied to many meteorological problems, such as predicting tornadoes (Marzban and Stumpf, 1996), quantitative precipitation (Hall *et al*., 1999) and even long-range monsoon precipitation (Wu *et al*., 2001). It has a strong potential for pattern reorganization and signal processing problems and also has the ability to predict values of the time series from itself. The tool, which is one of the most effective methods for pattern reorganization and signal processing problem, has been applied in this study to improve Indian Geostationary Satellite (INSAT) derived Quantitative Precipitation Estimates (QPE). Details of the ANN technique are available in the literature.

2. The sub-division wise weekly QPE prepared by the Satellite Division of India Meteorological Department (IMD) are used in this study. In order to get the compatible data sets of ground truth, the sub-division wise weekly rainfall data obtained from Hydrology Division has been used as observed data set.

In general, a neural network is a computer model composed of individual processing elements called neurons. The neurons are connected by links in terms of weights. A neural network may consist of multiple layers of neurons interconnected with other neurons in the different layers. These layers are referred to as input layer, hidden layer, or output layer. The inputs and the interconnection weights are processed by a weighted summation function to produce a sum that is passed to a transfer function. The output of the transfer function is the output of the neurons. A neural network is trained with input and output pattern examples. It then constructs a nonlinear numerical model of a physical process in terms of network parameters. The NN technique proposed here is based on the feed forward multi-layer structure.

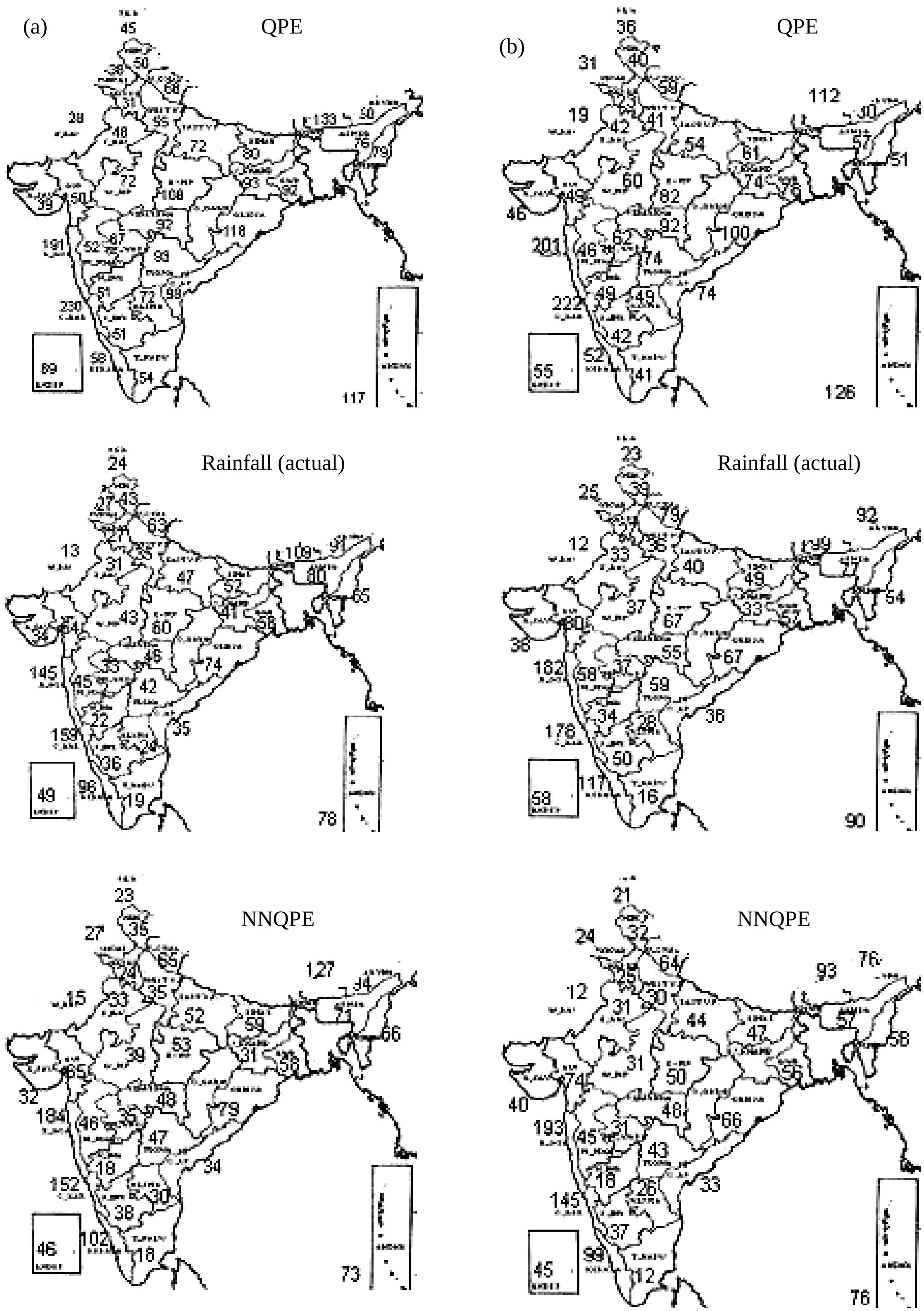
The weekly QPE form satellite observation of south west monsoon season 2001, 2003 and 2004 of a sub-division is taken as signal to the input layer neurons. Training was done with the help of corresponding weekly rainfall data of that particular sub-division and then finally the results were validated with another set of sample data for the year 2005.

For the inter-comparison of performance skill, the skill scores are obtained as

$$\text{Skill Score} = \left(1 - \frac{\text{RMSE}^2{}_{\text{NNQPE}}}{\text{RMSE}^2{}_{\text{QPE}}}\right) * 100\%$$

Where $\text{RMSE}_{\text{NNQPE}}$ and RMSE_{QPE} stand for RMSE of the neural network model and the satellite precipitation estimates respectively.

3. The mean pattern of sub-divisional weekly rainfall of southwest monsoon based on QPE, observation and neural network in respect of training sample and independent test sample are shown in Figs. 1(a&b). From the figures, it has found that the mean pattern of QPE does not agree with the observation for most of the sub divisions both for the training as well as for the test data period. The maximum over estimation occurs over Andaman & Nicobar Islands, Kerala, coastal Karnataka and east Madhya Pradesh. But with NNQPE the pattern becomes closer to the observation. The weekly mean



Figs. 1(a&b). The average pattern of QPE, rainfall and neural network with (a) training and (b) testing data period in monsoon season

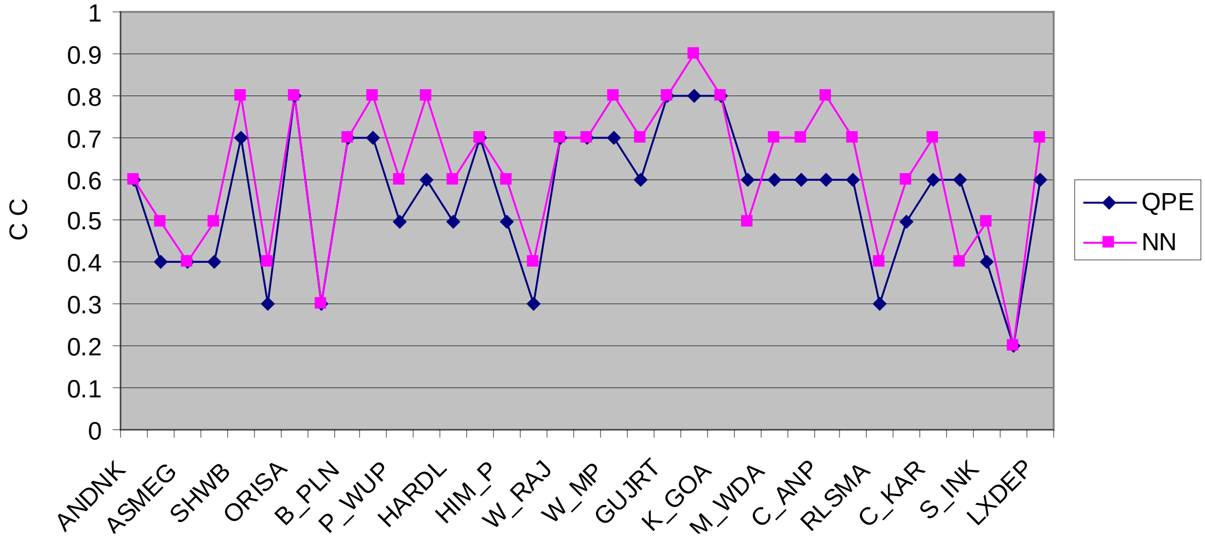


Fig. 2. The overall pattern of CC of QPE and NN with respect to the observed rainfall of all sub-divisions in the southwest monsoon season

range of QPE, actual rainfall observation and NNQPE for the training set are respectively 28-230 mm, 13-159 mm and 15-184 mm. The corresponding ranges for the test data set are 19-222 mm, 12-178 mm and 12-193 mm respectively.

Fig. 2 shows the overall pattern of co-relation coefficient (CC) of QPE and NNQPE with respect to the observed rainfall. The CC of NNQPE is found to be found higher over the most sub-divisions compare to QPE.

The performance skill of the NNQPE model for testing data period of the meteorological sub-divisions has been shown in Table 1. A positive value of skill score stands for a better performance of the model over satellite precipitation estimates, while a negative value of skill score indicates that the model does not have skill to match the satellite precipitation estimates. Though some of the sub divisions have smaller positive skills but this clearly indicate that the neural network model have overall positive skills and perform better than the conventional satellite precipitation estimates with training as well as independent data sets.

The error analysis indicates that for the lower range of QPE errors (QPE-Observed) (up to 30 mm), the percentage of the events in neural network is more, and also for the higher range of QPE errors (>90 mm) the events are less compare to the actual satellite precipitation estimates. That is errors are minimized from higher range to lower range in neural network model. This intern reveals that the performance of model is appreciably good over conventional technique.

4. In this study NN approach have been used to improve the quality of INSAT derived quantitative precipitation estimates over Indian region for the southwest monsoon season. The study shows that the neural network model is capable to provide improvement in the quality of sub-divisional weekly QPE. The weekly mean absolute error of QPE which ranges between 10-99 mm reduces to 4-70 mm in case of NNQPE. This indicates that the neural network approach reduces the QPE errors and provides the pattern which is closer to the observed rainfall pattern.

The inter-comparison skill scores confirm the better performance and effectiveness of the proposed NN model. The results have clearly indicated the feasibility of our approach. The approach shows encouraging results to reduce errors of satellite precipitation estimates. Further improvement can be achieved through the use of high quality daily rainfall analysis and suitable adjustment between cloud top temperature threshold and rain-rate. The ensemble neural network can be developed to perform multi-class classification with location and

TABLE 1

The quantitative error range and skill score of QPE and NN model the testing data period

Error range (mm)		0-30	31-60	61-90	> 90	Skill score (%)
Andaman & Nicobar Islands	QPE	59	18	6	17	61
	MODEL	70	12	12	6	
Arunachal Pradesh	QPE	26	41	0	33	43
	MODEL	41	23	23	6	
Assam & Meghalaya	QPE	53	35	12	0	-1.5
	MODEL	59	29	6	6	
Bihar	QPE	82	18	0	0	80
	MODEL	94	6	0	0	
East Rajasthan	QPE	88	12	0	0	78
	MODEL	94	6	0	0	
East Uttar Pradesh	QPE	76	18	6	0	50
	MODEL	94	6	0	0	
Gangetic West Bengal	QPE	47	47	6	0	49
	MODEL	65	29	6	0	
Haryana, Chandigarh & Delhi	QPE	88	12	0	0	51
	MODEL	82	18	0	0	
Jammu & Kashmir	QPE	71	6	23	0	46
	MODEL	94	0	0	6	
Jharkhand	QPE	47	29	18	6	59
	MODEL	53	18	29	0	
Nagaland, Manipur, Mizoram & Tripura	QPE	82	12	6	0	40
	MODEL	88	12	0	0	
Orissa	QPE	58	12	18	12	64
	MODEL	82	6	12	0	
Punjab	QPE	94	6	0	0	34
	MODEL	88	12	0	0	
Sub-Himalayan West-Bengal & Sikkim	QPE	59	23	12	6	47
	MODEL	76	18	6	0	
Uttaranchal	QPE	76	12	12	0	58
	MODEL	76	18	6	0	
West Rajasthan	QPE	94	6	0	0	73
	MODEL	100	0	0	0	
West Uttar Pradesh	QPE	65	29	6	0	61
	MODEL	82	12	6	0	
Himachal Pradesh	QPE	71	23	6	0	26
	MODEL	82	6	6	6	
West Madhya Pradesh	QPE	53	36	6	6	66
	MODEL	82	12	6	0	

TABLE 1(*Contd.*)

Error range (mm)		0-30	31-60	61-90	> 90	Skill score (%)
East Madhya Pradesh	QPE	0	0	35	65	1
	MODEL	0	76	6	18	
Gujrat Region	QPE	59	18	12	11	26
	MODEL	59	23	0	18	
Saurashtra, Kutch & Diu	QPE	94	0	0	6	65
	MODEL	88	12	0	0	
Konkan & Goa	QPE	18	29	12	42	39
	MODEL	29	24	18	36	
Madhya Maharashtra	QPE	47	29	24	0	30
	MODEL	65	22	12	1	
Marathawada	QPE	59	29	6	6	72
	MODEL	82	18	0	0	
Vidarbha	QPE	41	35	6	18	80
	MODEL	65	29	6	0	
Coastal Andhra Pradesh	QPE	18	0	0	82	97
	MODEL	82	18	0	0	
Telangana	QPE	47	29	12	12	45
	MODEL	70	18	0	12	
Rayalaseema	QPE	65	23	6	6	77
	MODEL	82	12	6	0	
Tamil Nadu & Pondicherry	QPE	71	23	6	0	83
	MODEL	88	12	0	0	
Coastal Karnataka	QPE	18	29	6	47	58
	MODEL	35	24	18	24	
North interior Karnataka	QPE	70	18	0	12	68
	MODEL	88	12	0	0	
South interior Karnataka	QPE	53	23	18	6	45
	MODEL	74	18	6	2	
Kerala	QPE	35	12	18	35	36
	MODEL	29	23	18	30	
Lakshadweep	QPE	65	23	12	0	3
	MODEL	59	29	12	0	

elevation information to improve the orography-affected areas.

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